

# Reaching Consensus Among Mobile Agents: A Distributed Protocol for the Detection of Social Situations

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**Abstract.** Physical social encounters are governed by a set of socio-psychological behavioral rules with a high degree of uniform validity. Past research has shown how these rules or the resulting properties of the encounters (e.g. the geometry of interaction) can be used for algorithmic detection of social interaction. In this paper, we present a distributed protocol to gain a common understanding of the existing social situations among agents.

Our approach allows a group of agents to combine their subjective assessment of an ongoing social situation. Based on perceived social cues obtained from raw data signals, they reach a consensus about the existence, parameters, and participants of a social situation. We evaluate our protocol using two real-world datasets with social interaction information and additional synthetic data generated by our social-aware mobility model.

## 1 Introduction

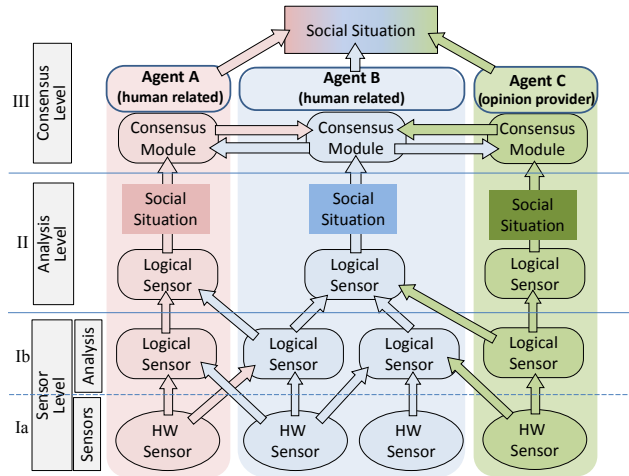
Mobile devices can be used to algorithmically detect social situations by combining and analyzing sensor information (e.g. [15,17,27,4,31,3]). To allow new and promising applications it is essential to detect social situations with low latency (i.e. during the social encounter). Furthermore, the detection on distributed devices and the agreement among these makes it viable for applications on personal mobile devices. Therefore Groh et al. [15] presented an approach based on Subjective Logic (SL) to share opinions regarding the existence of social situations among agents on different levels of abstraction (raw low-level sensor data, “sub-symbolic” probabilistic models and “symbolic” social situation models). We enhance this approach and designed a distributed algorithm to assess the boundaries of social situations among agents.

In section 2, we summarize the required foundations of social situations, briefly describe related work, and provide a short overview of Subjective Logic. In section 3, we present our approach to reach consensus regarding the existing social situations within a group of agents. In section 4, we describe our evaluation of the algorithm. We conclude with a summary in section 5.

## 2 Previous and Related Work

### 2.1 Social Situations

Adam Kendon’s F-formations and the concept of “o-spaces” are widely used to analyze social interaction patterns [25,26]. The term “o-space” refers to the circular area which is formed by a group of socially interacting people (standing in a circle, shoulder to shoulder). F-formations describe the spatial orientation of interacting individuals. Mathematically, a social situation  $S$  may be defined [15] as a tuple  $(P, \tilde{X})$ .  $P$  is a set of (unique identifiers for) socially interacting individuals who are fully mutually aware of their interaction and  $\tilde{X}$  is a spatio-temporal reference.



**Fig. 1.** Exemplary setting for distributed social situation detection

Groh et al. discussed [15] how evidence for social situations from several sensor sources can be exchanged and aggregated to algorithmically assess the existence of a social situation. Fig. 1 shows the basic elements of Groh et al.’s architecture for “social life networks” [18]. It illustrates a setting of two agents, each directly connected to a human individual and an infrastructure related agent that is only entitled to provide opinions (see discussion in section 3.7). Recent studies [27] demonstrated how smartphones can be used as agents for distributed social sensing.

The architecture has three conceptual layers: the sensor level consists of a set of hardware sensors (e.g. microphones, gyroscopes) providing raw data from the agent’s environment. Raw data is aggregated using sensor fusion to either enhance quality of measurement (e.g. by using competitive fusion for dependent opinions, i.e. measuring the same environmental phenomenon with different

means) or increase the span of information (e.g. by including additional information not covered by the other sensor) [8, p. 32ff]. Some sensors may be better characterized as an abstraction of a group of hardware sensors (and therefore are part of layer Ib) while others include higher levels of analysis (and thus belong to layer II). Layer II sensors are expected to output the agent’s subjective assessment of the user’s current social situation. Since a social situation requires full mutual awareness of the social situation’s existence among the proposed participants, layer III consists of a consensus module allowing the agents to gain a common understanding of their social situation. Groh et al. [15,16] evaluated the layers I and II but did not consider a simulation of layer III. In section 3, we propose a concrete algorithm to establish consensus on social situations.

## 2.2 Agreeing on Social Situations

*Consensus finding* In agent networks the term “consensus” refers to “reach[ing] an agreement regarding a certain quantity of interest that depends on the state of all agents” [29]. Consensus problems have a long history reaching back to 1960s [11]. Applications include flocking / swarming, sensor fusion, random networks, synchronization of coupled oscillators, etc. A comprehensive overview is provided by Olfati et al. [29]. With upcoming car-to-car communication, certain aspects have been revisited with high economic interest. Well-known protocols to find consensus include simple quorum-based approaches (the option receiving the majority of votes is seen as consensus), classical leader-follower architectures (all other agents adopt the opinion of the leader), iterative approaches like the one presented by DeGroot [11] where each agent revises its position after seeing the others’ opinion, or the Monotonic Concession Protocol [36] which allows finding an optimal consent for two agents with different utility functions. While consensus problems appear in various fields, to the best of our knowledge, consensus regarding existing social situations in social ad hoc networks has not been addressed.

*Clustering of ad hoc networks* Traditional distributed clustering algorithms often present a solution to locally cluster data which is distributed across several nodes. Therefore, data gets clustered locally and results are aggregated afterwards. These approaches are not applicable for our scenario as we wish to cluster the set of agents itself.

Clustering of ad hoc networks corresponds roughly to our problem statement. Clustering in ad hoc networks is mostly driven by designing sophisticated routing mechanisms [19,37] – the fundamental idea is that data dissemination in networks is faster and causes less effort when a multi-hop clustered topology is used. Each cluster has a cluster head coordinating the cluster. Different methods to nominate a cluster head are discussed by Chatterjee et al. in [9]. Most clustering approaches distinguish between two phases: a set up phase where the agent set is clustered and a maintenance phase to adopt the clustering to the changing topology of the network (e.g. due to moving or breaking nodes). For further details, please consider [1,2,34,38] as an exemplary list of surveys on this topic.

### 2.3 Subjective Logic

Subjective Logic [23,24] is an enhancement of the Dempster-Shafer theory of evidence [33]. Its main goal is to express uncertainty and subjectivity of statements made by agents. Assuming an atomic world state space  $\Theta = \{x_1, x_2, \dots, x_n\}$ , in *first order logic*, an agent's assessment of the world's state is either true or false. Subjectivity can be modeled by including statements of several agents. However, it is hard to model uncertainty. *Classic probability theory* allows to model uncertainty but lacks subjectivity. Thus, it is difficult to combine statements from an a-priori unknown set of agents.

A Belief Mass Assignment (BMA)  $m : 2^\Theta \mapsto [0, 1]$  assigns a belief mass  $m(x)$  to a subset  $x \subseteq 2^\Theta$  so that  $m(\emptyset) = 0$ ,  $m(x) \geq 0$  and  $\sum_{x \in 2^\Theta} m(x) = 1$ . An agent's belief in the statement "the world is in state  $\eta$ " is expressed as  $b(\eta) = \sum_{\eta' \subseteq \eta} m(\eta')$ .

A simplified Dirichlet BMA (DBMA) assigns belief mass only to atomic states and  $\Theta$  as a whole, i.e.  $b(x) \neq 0 \Rightarrow (x \in \Theta) \vee (x = \Theta)$ . Thus, an agent has a corresponding belief and an uncertainty (expressed by assigning belief to  $\Theta$ ). The base rate  $a : \Theta \mapsto [0, 1]$  can be interpreted as an assignment of a-priori probabilities for each state. A multinomial opinion of an agent  $A$  about a state  $x$  is defined as a tuple  $\omega_x^A = (b, u, a)$  based on a DBMA. The expected value of a state  $x$  can be calculated by using the probability expectation function  $p(x) = b(x) + a(x)u$ . It is comparable to a posterior probability. A binary opinion about a state  $x$ , denoted as  $\omega_x = (b = b(x), d = b(\bar{x}), a = a(x))$ , is a multinomial opinion over a binary set  $\Theta = \{x, \bar{x}\}$ . The belief in  $\bar{x}$  can therefore be interpreted as disbelief in  $x$  (written as  $d(x)$ ).

The cumulative fusion operator  $\oplus$  combines independent opinions (e.g. observations covering disjoint time intervals), whereas the averaging fusion  $\oplus$  operator is used to combine dependent opinions (e.g. observations covering the same time interval). For a more detailed explanation, please refer to [24,15].

## 3 A Distributed Protocol for Consensus on Social Situations

### 3.1 Basic Concept

Reaching agreement about social situations among agents corresponds to agreeing on clustering of nodes of a network only by means of local knowledge. Therefore, the terms "cluster" and "social situation" are used synonymously in this section (the same applies to "agent" and "node"). Since a multi-phase protocol including a set up and maintenance phase (as often used to cluster ad hoc networks) is not practicable for a long running and constantly changing stream of social situations we decided to use a protocol involving an arbiter. Clusters are formed using an incremental process adding agent after agent to a cluster. Agents who want to join a cluster trigger a new agreement process where both parties (the joining agent and the group of agents in the existing social situation)

need to agree. This procedure corresponds to the emergence of real-life human social situations. As in real life, social situations can merge.

Each social situation with  $n$  members consists of one cluster head and  $(n - 1)$  members (with  $n \geq 1$ ). The algorithm starts with every agent  $i$  being in a social situation with itself and therefore being the cluster head of its unary cluster  $c_i = \{i\}$  ( $i$  represents a unique identifier for this agent).

Each cluster head  $i$  can decide to ask another agent  $j$  to agree on being in a joint social situation. If  $j$  agrees,  $i$  changes its role to cluster member and  $j$  becomes new cluster head of the joint social situation (which is then referred to as  $c_j$  since  $j$  is the new cluster head). Cluster members remain passive, requests received to initiate social situations are forwarded to their respective cluster head. Cluster members periodically broadcast opinions about ongoing social interactions between pairs of nodes to all other nodes within communication range. This is done using “member messages”  $m_{cm}$ . Each cluster head collects this information, periodically combines it with its own opinions (using the SL formalism discussed in section 2.3), and broadcasts the resulting group structure of its cluster in a “cluster head message”  $m_{ch}$  to all members of its cluster (and thus to all agents belonging to the cluster head’s social situation).

If a member  $i$  leaves a social situation, the cluster head will reflect this by not listing  $i$  in the member list of the next cluster head message  $m_{ch}$ . The affiliation of agent  $i$  to a social situation is decided by the cluster head based on the group’s opinion. If the cluster head itself leaves the social situation, the cluster breaks: A non-existent cluster head causes an absence of the periodically sent  $m_{ch}$  message for a given period of time. This is a signal for the affected member agents that the cluster is broken, i.e. the social situation has ended. In both cases an agent not associated to any cluster forms its own cluster again and changes its role back to cluster head.

### 3.2 Message Types

**Member messages**  $m_{cm}$  are sent by cluster members for two reasons: to inform the environment (i.e. the nodes within communication range) about the agent’s assessment of the existing social situations and to inform the cluster head that the sending member is still within reach (keep alive function). The message contains one or more opinions about agents being in a (pairwise) social situation, i.e.  $m_{cm}$  sent by agent  $o$  in cluster  $c_p$  consists of  $o$ ’s identifier, the identifier of  $o$ ’s current cluster head  $p$ , and an arbitrary number of tuples  $(i, j, \omega_{i,j}^o)$  with  $\omega_{i,j}^o$  being  $o$ ’s SL opinion about the existence of a social situation between agents  $i$  and  $j$ . In a very trivial case with only one single opinion as part of the message,  $m_{cm}$  is a tuple  $(o, p, (i, j, \omega_{i,j}^o))$ . The identifier of the current cluster head is included to allow the cluster head to recognize if agents make false assumptions about their cluster head. Usually an agent sends information concerning all agents within a socially relevant distance. A distance of approx. 10m would be ideal [35]. If correspondingly accurate absolute device localization is not available, approximate relative positioning e.g. with the help of Wifi or Bluetooth is also possible [27]. The message is sent with an agreed minimum frequency which

can pragmatically be adjusted to the typical dynamic range of human social situations (e.g. 1Hz) to allow the cluster head to recognize when a member node has left the cluster.

**Cluster head messages**  $m_{ch}$  are sent by cluster heads. As for the member message discussed above, the purpose is twofold: 1) Propagate the knowledge about the social situation that is managed by the emitting cluster head and 2) inform the members of the cluster that the cluster is still alive. The message can be described as a tuple  $m_{ch} = (p, c)$  with  $p$  being the unique identifier of the cluster head and  $c$  being the set of identifiers of the cluster's members. The set  $c$  is built based on the preceding agreement process (i.e. the aggregation of the member messages  $m_{cm}$  and the cluster head's opinion). Since the underlying network is dynamic due to agent movement, the message needs to be sent periodically by the cluster head with a fixed frequency  $f_{min}$  to indicate that the cluster still exists.  $f_{min}$  can also be adjusted to typical human social situation dynamics. Member agents recognize that they are out of communication range or left the cluster when they do not receive a  $m_{ch}$  message for a time  $t > T = 1/f_{min}$ .

**Request messages**  $m_{req}$  are sent by cluster heads only. Their purpose is to request agents to agree on being in a joint social situation. The message can be described as  $m_{req} = (p, c)$  with  $p$  being the unique identifier of the cluster head and  $c$  the set of identifiers of the other agents in the respective cluster. Pragmatic agents only request social situations if the corresponding aggregated belief reaches an appropriate threshold and if the other agent is within a socially relevant distance to reduce energy consumption.

**Response messages**  $m_{res}$  are sent as a reaction to a request message  $m_{req}$ . They inform the requesting party whether the request was accepted or not. If the request was accepted, the *requesting node* changes its status from cluster head to cluster member. The new cluster head of the extended social situation is the *accepting agent*. If the request gets declined, two cases are distinguished: 1) If the requested agent declines the request since it is not allowed to manage the social situation (i.e. it is only a member and not the cluster head), the negative reply includes the identifier of the cluster head of the agent's social situation and all of its members. In this case, the requesting node evaluates whether a social situation with the complete cluster of the requested agent is feasible. If this is the case, the request will be sent again to the cluster head of the respective social situation. 2) If the requested agent declines the request because it does not believe to be in a social situation with the requester, the requesting agent stores this information for a certain period of time to avoid sending the request again.

### 3.3 Agent Programs

Algorithm 1 shows the main process running on all agents. Each agent starts in a separate cluster as a cluster head. The agent periodically sends either a  $m_{ch}$  message in case it is cluster head or a  $m_{cm}$  message if it is member of a cluster using a fixed time interval  $T$ .

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**Algorithm 1:** Agent’s main program skeleton

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```
 $c \leftarrow \{ownID\}, chID \leftarrow ownID, clusterhead \leftarrow true$  while  $true$  do  
  if  $clusterhead$  then  
    if  $\|c\| \geq 1$  then  
       $send(m_{ch})$   
    end  
  else  
     $send(m_{cm})$   
  end  
   $wait(T)$   
end
```

---

*Request sending and processing* In addition to the main loop each agent starts a second procedure in parallel, shown in algorithm 2, to send requests to extend the social situation (as mentioned above, this is only possible if the agent acts as a cluster head). The function *getCandidateForSocialSituation()* returns a list of candidates to extend the current social situation (based on the aggregated opinions derived from the other agents’  $m_{cm}$  messages). In case the candidate accepts the request, it becomes the new cluster head, and the original sender of the request becomes a cluster member of the extended social situation. In case the addressed agent declines the request since it is not the cluster head (and forwards the requester to its cluster head), the requester checks whether it is feasible to merge both social situations (part of function *check()* in algorithm 2). In case the agent declines because it does not believe in a social situation with the requesting cluster head, the requesting cluster head marks this request as failed to prevent flooding the agent with requests.

Algorithm 3 illustrates how an agent replies to a received  $m_{req}$  message: in case the agent is the cluster head of its social situation, it checks whether an enhanced social situation with the sender of the message is likely (determined based on the aggregated subjective logic opinions of the other agents in *checkForSocialSituation()*), and sends a positive response message  $m_{res}$  in the positive case. If *checkForSocialSituation()* returns *false* (i.e. the existence of a social situation between the requester and the current cluster is unlikely), a negative response message  $m_{res}$  is sent. If the agent which received the request is not a cluster head, it replies with a negative response message pointing the sender to the cluster head of its social situation.

*Member exclusion* It is important that the cluster head controls the set of members of its cluster: if agents leave the cluster, the set of agents within the cluster propagated in the  $m_{ch}$  messages gets adjusted.

### 3.4 Making Decisions

In section 3.3, decision making was shifted to the functions *getCandidateForSocialSituation()* (Algorithm 2) and *checkForSocialSituation()* (Algorithm 3). There

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**Algorithm 2:** Request sending

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```
while clusterhead do
   $ID \leftarrow \text{getCandidateForSocialSituation}()$ 
  if  $ID \neq \text{null}$  then
    send( $m_{req}$ )
     $m \leftarrow \text{receive}(m_{res})$ 
    if  $m = \text{positive}$  then
       $clusterhead \leftarrow \text{false}$ 
       $chID \leftarrow \text{senderID}(m)$ 
    else
      if  $m = \text{forward} \wedge \text{check}(\text{senderID}(m), \text{forwardToID}(m))$  then
        setAsNextCandidate( $\text{forwardToID}(m)$ )
      else
        markRequestAsFailed( $\text{senderID}(m)$ )
      end
    end
  end
end
waitAPeriodOfTime()
end
```

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**Algorithm 3:** Request processing

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```
if clusterhead then
  if  $\text{checkForSocialSituation}(m_{req})$  then
    | send( $m_{res} \leftarrow (\text{true})$ )
  else
    | send( $m_{res} \leftarrow (\text{false})$ )
  end
else
  | send( $m_{res} \leftarrow (\text{false}, chID)$ )
end
```

---

are two possible ways to aggregate the information and come to a discrete yes-no-decision: 1) discretize the SL opinions already on agent-level and aggregate yes-no-opinions later or 2) aggregate the SL opinions and discretize later.

An early discretization has the benefit of early simplification: A very skeptic agent would only decide in favor of a social situation if the social situation can be pairwise confirmed for all potential members. In contrast, a more gullible agent would vote in support of a social situation even if not all members are confirmed pairwise.

In contrary, first combining and then discretizing (and thus deciding) offers the benefit of a more differentiated decision since the confidence of the individual opinions is considered. Ignoring a single agent with slight disbelief in favor of four agents with strong opposite belief seems reasonable, but sparing an agent with a strong belief in favor of four agents with only slight opposite belief is a less favorable option.



Discretization results in a loss of information and therefore should be done as late as possible in the decision process. Thus the latter approach should be preferred. The individual opinions of all agents within a cluster  $c_i$  about being in a social situation with the members of a cluster  $c_j$  can be combined using the averaging fusion operator  $\oplus$  for SL opinions [24,15] to build a group opinion  $\omega_{c_i, c_j}^{c_i} = \oplus_{x \in c_i, y \in c_j} \omega_{x, y}$ . After aggregating, the result needs to be discretized using a decision function  $f_{\boxplus}$  [15] to allow a mapping to a concrete decision.

### 3.5 Conflict Resolution

Two agents may send requests to each other exactly at the same point in time. Thus both would be willing to accept the other's request. This leads to a conflict as both agents assume to be the new cluster head. To mitigate this risk the function *checkForSocialSituation()* in algorithm 3 needs to check whether the requesting agent is an agent which has been requested to join the social situation previously and which did not reply yet. If this is the case, the agent with the identifier being closer to the hashed concatenation of both identifiers is the new designated cluster head.

### 3.6 Message and Time Complexity

An upper limit of potential communication partners should exist to ensure scalability [13]. An agent only contacts other agents if they are either candidates for a social situation or part of its current social situation (both limited locally). Given  $n$  agents within communication range, the maximum number of messages within a time interval  $t$  is in any case lower than  $(2n + 1) \cdot (t/f_{min})$  consisting of  $n$  request messages  $m_{req}$ ,  $n$  response messages  $m_{res}$ , and one cluster head or cluster member message per cycle with frequency  $f_{min}$ .

An agent stores the current social situation, the identifiers of agents which denied a request for a social situation, and the identifiers of agents which did not reply to a request to avoid race conditions. The required storage space depends on the number of agents involved, with an existing upper bound  $n$  since the number of candidates for a social situation is physically limited. All stored information are only kept for a limited time limit. Thus, the required storage space does not increase over time.

### 3.7 Optimizations and Variations

*Detach agents from individuals* In a real-world scenario it is more realistic to assume that some individuals are not represented by an agent and even that some agents are not associated with any individual but are fixed at a specific location. Allowing to split agents and human individuals requires an extension of the identifier concept: Agents and human individuals which are physically linked ("human related agents") share an identifier. Individuals without an agent have an identifier which allows postulating opinions about social situations for the

respective human individual. Agents without an associated human individual (“opinion providers”) can only provide opinions but cannot be part of any social situation. This leads to an extended notion of the cluster head message  $m_{ch}$  as the message format has to contain information about real human individuals:  $m_{ch} = (ch, c_a, c_h)$  with  $c_a \subseteq c_h$  being the set of all agents in the cluster and  $c_h$  being the set of all human individuals. Opinion providers are not involved in the membership process – they can only send their opinions using  $c_{cm}$  messages. A trust concept (like the one proposed by Bamberger et al. [5]) can support the decision which opinions to consider to which degree in building the aggregated group opinion. It is assumed that all agents can identify a human individual as a single person with a single unique identifier, that agents can recognize whether humans are equipped with a physically connected agent and whether an agent is an opinion provider or a real agent. Recognition of human individuals has to be implemented on a lower architectural level, as it was investigated e.g. in [30].

*Pseudonyms and identities* In a Sybil attack a reputation system is subverted by forging identities [28,12]. Any capability of dealing with a certain percentage of malicious acting nodes can be subverted by forging identities. This can be mitigated by adding only trustful identities and therefore limiting the number of identities per node. Trustful identities are usually managed with the help of a trusted third party acting as a trust anchor for all agents, handing out identities that are certified through signatures based on asymmetric cryptography. Approaches to avoid Sybil attacks without a trusted third party are based on the assumption that the attacker’s resources are limited, see e.g. [12]. These approaches successfully prevent mote-class attacks which use a normal network node. They perform badly in homogeneous network structures and against laptop-class attacks with potentially unlimited resources.

*Avoiding to request cluster members for social situations* Sending request messages to an agent which only has member status within a social situation results in a negative response message. To avoid this unnecessary step every agent should use logged cluster head messages of social situations to gather an impression about the structure of ongoing social situations and send requests directly to the respective cluster head.

*Limitation of opinion weights* Lower uncertainty can be interpreted as higher weight of an opinion when aggregated using the averaging fusion operator  $\oplus$ . In order to avoid malicious agents increasing their impact on the system, minimum levels of uncertainty have to be defined for opinion authors.

*Keeping clusters stable* Instead of dispersing the cluster, a leaving cluster head could nominate a member agent as a replacement cluster head. As a first action, the new cluster head would send an  $m_{ch}$  message to establish a new cluster with the same members (but without the previous cluster head). Possible criteria for selecting a replacement cluster head might be the agent’s energy level or the average time within the social situation. This would leverage the observation that

agents which move quickly between social situations would perform poorly as cluster heads (as it is likely that they leave the social situation quite soon) [9,6].

In addition to the extensions listed above, we are aware of a remaining point of criticism: Whenever an agent postulates an opinion about two other agents, this opinion is usually not taken into account unless one of the two agents is within the same social situation as the postulating agent. The protocol does not fully leverage this knowledge as we assume that this has already happened on the analysis level (cf. Fig. 1).

## 4 Case Study

We simulated the proposed protocol based on numerous datasets of social interactions. Each agent was equipped with SL opinions about being in a social situation with each other agent. Without any conceptual restriction to a classifier, we generated the SL opinions with the Gaussian Mixture Models (GMM)-based classifier that was described in [16]. The classifier uses the relative distances and shoulder angles as input parameters. We use Rand Index [32], Adjusted Rand Index [22], and Jaccard Index as a distance measure between the partitions generated by our proposed protocol and the actual social situation clusters.

### 4.1 Dataset 1 (DS1)

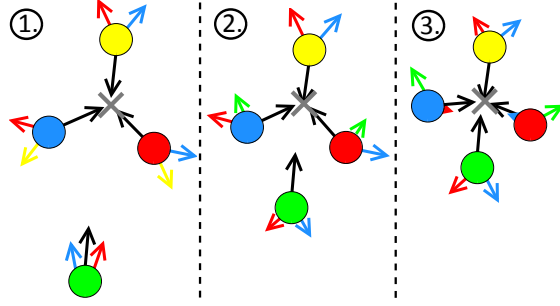
The first dataset [17] contains geometry data of social interaction and was captured with infrared beacons that were fixed on the shoulder of each of the nine interacting participants. Eight cameras tracked the social interaction between the participants. The tracking accuracy was  $< 1mm$  and  $< 1^\circ$  (cf. [17]). Out of the captured data pairwise relative shoulder angles and pairwise relative spatial distances have been computed for all participants to reveal a correlation between those parameters and the existence of a social situation.

### 4.2 Dataset 2 (DS2)

The second dataset [10] covers two coffee break scenarios which were used in [30]. They were captured by a single camera. For our case study, we rely on the positions and orientations of the individuals that were algorithmically computed based on the recorded images (cf. [30]). We computed the corresponding relative shoulder angles and distances among the participants as input to our simulation.

### 4.3 Synthetic Data

We enhanced the ad hoc group simulator SUMI [14] to support the generation of social situation data. SUMI combines group and node mobility models that simulate individual Gauss Markov motions of the nodes. Each node makes a random walk until a random group is formed. Once all members have arrived, they wait until the group ends or performs a group motion. In comparison to



**Fig. 2.** Group positioning in enhanced ad hoc group simulator SUMI: resting group with 3 members is joined by a fourth member

the original version, node speed has been reduced to walking speed, movement speed selection strategy has been replaced by a Markov chain and resting times have been replaced by a force model for the arrangement of nodes in social situations (inspired by [7,21,20]). Fig. 2 shows positioning of a resting group with three nodes when a fourth node joins: “x” denotes the group centre, which attracts all agents. Due to the repelling effect between the agents, each agent is exposed to the repelling forces of the next two agents. The color of the arrows in Fig. 2 indicates the force’s origin. Shoulder angles are set either with a probabilistic chosen random deviation to the group center or in the moving direction in case of moving groups. Synthetic data has inherent information about the social situations while DS1 and DS2 were annotated manually.

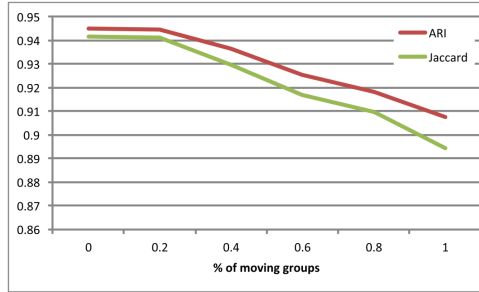
#### 4.4 Evaluation

Index	DS1		DS2 (1)	DS2 (2)
	AVL[17]	Proposed protocol		
Rand	0.766	0.796	0.910	0.960
Index	$\pm 0.20$	$\pm 0.21$	$\pm 0.06$	$\pm 0.02$
ARI	0.529	0.571	0.093	0.116
	$\pm 0.37$	$\pm 0.40$	$\pm 0.19$	$\pm 0.20$
Jaccard	0.67	0.659	0.074	0.082
Index		$\pm 0.31$	$\pm 0.13$	$\pm 0.13$

**Table 1.** Key figures for DS1 & DS2

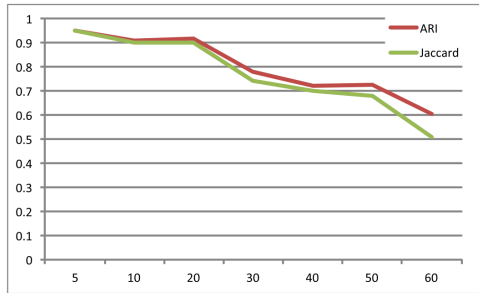
Tab.1 shows the comparison between real social situations and the social situations as agreed by our protocol, averaged for the complete simulation, for DS1. We compared the results with the social situations that have been detected by a central clustering approach (AVL) in [17]. To ensure comparability,

the central clustering approach (AVL) and our proposed protocol used the same SL opinions (which had a correct classification rate of  $\sim 75\%$  only [17]). Considering the fact that the benchmark values (AVL) have been achieved using global knowledge, we demonstrated that social situation detection using local knowledge (i.e. our proposed approach) performs at least equivalently. Both sequences of DS2 lead to poor correct classification rates when using the GMM of [17] to generate the SL opinions. This can be explained by various reasons: While the first dataset (DS1) was captured using infrared tracking, the second dataset (DS2) relies on less granular orientation data acquired using image recognition. The foot position is calculated based on the head position and a height estimation. This results in quite imprecise distances, varying from 16 cm up to 1.83 m within a social situation. With a recall of  $\sim 50\%$  only half of the social situations have been recognized. In [30] where the dataset was used originally, both sequences showed better results for precision and recall (DS2(1): precision 66%, recall 67%; DS2(2): precision 85%, recall 57%). We conclude that the accuracy of the underlying sensor information is an essential parameter when formulating an appropriate SL opinion in the logical sensors.



**Fig. 3.** Influence of the ratio of moving groups

*Synthetic Data* Fig. 3 shows Jaccard Index and ARI in relation to the moving group ratio. Rand Index is not included as it was close to 1 for all simulations on synthetic data due to the high number of singletons in the data. Those singletons are clustered correctly by default and therefore influence the result positively. In addition to a varying ratio of moving groups, we also investigated the effect of crowdedness. Fig. 4 shows Jaccard Index and ARI in relation to the number of simulated agents. The success of the proposed protocol is highly dependent on the quality of the underlying SL opinions. Moreover it is shown that the GMM works well on datasets with low density. If the scenario gets more crowded the number of false positives (FP) rises significantly. We recognized a high number of FP (increasing with the number of agents): 2,228 FP for 10, 14,329 FP for 20, and 32,667 FP for 30 agents (simulation of 15 minutes within  $50 \times 50$  meters).



**Fig. 4.** Influence of the closeness of agents

Possible reasons are 1) that the dataset generator does not pay any attention to collision avoidance what causes nodes getting close to each other randomly as if they were in a social situation and 2) that moving groups are not labeled as social situations when two agents are waiting for a third agent to join (however, they are recognized as social situations by the GMM).

## 5 Conclusion

Our main goal was to model the continuous process of forming, changing, and resolving of social situations. Therefore, we introduced a distributed protocol to gain a common understanding of the existing social situations among a group of agents. The protocol relies on the aggregation of subjective opinions represented using SL. The evaluation demonstrated that it is sufficient to have local knowledge to detect social situations since the proposed protocol performed not worse than traditional cluster techniques requiring full global knowledge of the graph. We demonstrated that the quality of the underlying SL opinions is the limiting factor for the resulting classification quality. Future challenges include scenarios with systems that are able to deal with more inaccurate data to allow real-world applications (e.g. a smartphone in a pocket is unlikely to provide the same data accuracy as a commercial infrared tracking system). In addition, techniques to compare partitions of sets like Rand Index might not be the right measure to compare different clustering results as they punish unimportant delays of social situation detection due to time discretization.

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